From the Ground Up: Labor Demand and Intergenerational Mobility in the US

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Abstract

We provide evidence on the impact of local labor market shocks on the intergenerational mobility measurements described in Chetty et al. (2014). We show that the fracking boom and Chinese import competition led to substantial changes in upward social mobility, and that between 10-15 percent of the spatial variation in absolute upward mobility can be explained by these two geographically concentrated shocks alone. Our results demonstrate that (1) an industry-specific shock can explain a comparable share of the variation in mobility as individual social factors and (2) these mobility measures are influenced by shocks that occur between measurement of child and parental income.

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I Introduction

The belief that a person's fate is not determined by the circumstances of their birth is a cornerstone of the American Dream and endures as a national ideal. However, Chetty et al. (2014), providing one of the most well-known measures of intergenerational mobility in the U.S., shows that there are stark differences in average outcomes for children born to similar parents. For instance, the probability that a child reaches the top fifth of the national income distribution if they were born to parents in the bottom fifth is 9.5 percent in Pittsburgh, but only 5.1 percent in Cincinnati, a city of similar size only a four and a half hour drive to the west.[1]

While much of the discussion of these place-based disparities has focused on segregation, education, family stability, and social capital (Chetty et al., 2014; Chetty and Hendren, 2018), we consider the role of large labor demand shocks that impacted the children identified in the Opportunity Atlas as they were reaching adulthood. Unlike previous cohorts, this group entered the labor market as two large changes were reshaping opportunities for workers in America: China's entry into the World Trade Organization (WTO) and the fracking boom. Increased import competition with Chinese goods contributed to the fall of manufacturing employment from a relatively stable 18 million over the previous decades to just 12 million nearly 10 years later. Meanwhile, the creation of new techniques to extract oil and natural gas allowed previously inaccessible reserves led to a production boom; Bartik et al. (2019) estimate that local households have an annual willingness-to-pay of \$1300-\$1900 to allow fracking, even accounting for lost amenities.

We show the visual relationship between these shocks and the two main measures of intergenerational mobility from Chetty et al. (2014) in Figure 1. Figure 1a maps "absolute upward mobility"[2] across commuting zones (CZs)[3], which measures the relative success of a child born to poor parents in a specific CZ. This measure can be interpreted as the average spot in the national income distribution a member of the 1980-82 birth cohort reaches if they are born to parents at the 25^{th} percentile of the national *parental* income distribution. Figure 1b maps "income persistence": the linear relationship between a parent's income rank and their child's rank. These data come from the Opportunity Atlas, a highly cited project by both academics and the popular press which documents

[1] In a world where parental income played no role in determining children's income, the probability of ending up in the top income quintile is mechanically 20 percent, so these differences are substantial.

[2] Higher absolute mobility represents better outcomes for children born to poorer parents relative to the national average outcomes of similar children. Absolute mobility does not rise because more well-off children in that area are doing worse.

[3] Commuting zones are aggregations of counties meant to approximate local labor markets. Tolbert and Sizer (1996) use county-to-county commuter flows to construct geographic boundaries which typically encompass four counties, and on average include just under 400,000 individuals.

spatial inequality in the United States.

In Figure 1c, we show a measure of total fracking production driven by exogenous geographic characteristics from 2001 to 2012.[4] A map of shale plays, the vast rock formations that trap oil and natural gas extracted via fracking is overlaid on top of our production measure. In Figure 1d, we map the *WTO Gap*, an employment weighted measure of Chinese import competition, as captured by the difference between protectionist and free-trade tariff schemes.

The similarity of these maps to the absolute mobility map is correlational, but suggests that changes to local labor markets could have downstream effects on mobility. Both shocks represent quasi-natural experiments, where some communities, like those in Western Pennsylvania near Pittsburgh and North Dakota enjoyed the boost in economic activity while being relatively insulated from Chinese competition. On the other hand, communities such as the Southeast and Cincinnati in the Rust Belt experienced a sizable negative shock to manufacturing employment, and were unaffected by the fracking boom due to uncontrollable geological factors.

Crucially for the mobility measures from the Opportunity Atlas, parent's household income is measured from 1996-2000, before fracking technologies were adopted, and before new tariff rates were permanently established. Children's household income is measured from 2011-2012, during which time all shale plays had begun using fracking technologies and production was undergoing large and sustained growth, as summarized in Figure 2a. Conversely, we can see an immediate, sharp decline in manufacturing employment that bottomed out in 2011 in Figure 2b. This timing means that parents were unable to take advantage of fracking jobs while their children were entering young adulthood (15-20 years old), meaning their income for the subsequent mobility measures was unaffected by either shock. Children, however, were largely able to benefit directly from the boom or be hurt by the bust in their early adulthood (30-32 years old), when their income is measured.

Using variation in fracking potential driven by exogenous geological variation, we find that, on average, areas of the country which benefit from the fracking boom are more upwardly mobile. Specifically, children born to low-income parents in boom areas are 2.4 percentage points higher in the national income distribution than their peers, who on average reach the 44^{th} percentile.[5] These effects are almost entirely concentrated among boys. Boys born to low-income parents in areas that would experience a fracking boom can expect almost 10 percent higher individual incomes than similar children who grow up elsewhere. The changes are even more substantial in the opposite direction for the manufacturing bust than the fracking boom; though this effect is driven primarily

[4] Measures for simulated fracking production and exposure to Chinese import competition are discussed in detail in Section II.

[5] This value is similar to the aggregate effects on earnings (and employment) attributable to the fracking boom using a panel of all US counties from 1996 to 2012, as shown in Appendix Figure A1.

by across state rather than within state variation.

Chetty et al. (2014) argue that since spatial differences in mobility track closely with social factors like college attendance, minority prevalence, and teen birthrates, mobility may be primarily driven by community-level behavior and culture rather than labor market conditions in adulthood.[6] To get a sense for how the boom and bust compare with social characteristics like segregation and marriage rates, we show using a variance decomposition exercise that geological factors amenable to fracking (despite being localized) explain roughly 5 percent of the national variation in mobility rates for children born to low-income parents, comparable to the amount explained by the fraction of Black residents. Exposure to Chinese import competition explains almost double the national variation. Within areas that actually had fracking production, this geological variation is the third-largest explanatory factor of absolute mobility, behind marriage rates and commuting times. We also confirm that these results are not driven by differences in pre-existing conditions across boom and bust areas.

A large literature identifies several strong predictors of variation in upward mobility across areas in the United States including differences in poverty and school quality (Chetty et al., 2014), income inequality (Corak, 2013; Durlauf et al., 2022), racial segregation (Derenoncourt, 2022), family structure (Chetty and Hendren, 2018), violence and crime (Sharkey and Torrats-Espinosa, 2017; Manduca and Sampson, 2019), pollution exposure (Colmer et al., 2023) and social capital (Chetty et al., 2022). These results point towards the importance of labor market characteristics for explaining the spatial heterogeneity in mobility documented by the Opportunity Atlas. While additional factors clearly play a large role, these two labor market shocks to low-skill male employment rival common measures in the literature in terms of explanatory power. While the Opportunity Atlas focuses on non-labor market characteristics of place, other work, including Katz and Kearney (2006) and Autor (2010), have highlighted the role that skill-biased technological change and declining opportunities play for low- and middle-income workers, suggesting instead that local labor markets are a crucial factor in shaping achievement. Our work complements these papers, showing that variation in labor demand for low-income workers has intergenerational consequences, implying that declining opportunities may compound on each other over time.

Another strand of literature has explored the social and family formation impacts of the fracking boom (Kearney and Wilson, 2018) and the manufacturing bust (Autor et al., 2019). Black et al. (2013) found that marriage and fertility increased during the coal boom of the 1970's, while Autor

[6] "The spatial patterns of the gradients of college attendance and teenage birth rates with respect to parent income across CZs are very similar to the variation in intergenerational income mobility. This suggests that the spatial differences in mobility are driven by factors that affect children while they are growing up rather than after they enter labor market." - page 3 of Chetty et al. (2014).

et al. (2019) find the opposite changes followed manufacturing job destruction in response to Chinese competition. These findings imply that the social conditions which can aid or hamper mobility are, at least in part, downstream of labor market opportunities. We add to this literature by directly studying the changes in mobility that occurred following these booms and busts. In particular, we highlight the unequal geographic effects of Chinese import competition, complementing Fort et al. (2018), who emphasized that *prior* to 2000, manufacturing employment had been growing in the South Atlantic.

Finally, our results point to the potential effectiveness of place-based policies that spur labor demand. Kline and Moretti (2014b) and Bartik (2020) argue for the efficacy of interventions which target labor demand in local labor markets. In related work, Kline and Moretti (2014a) document the long-run benefits of regional development programs by documenting the effects of the Tennessee Valley authority. Our paper contributes to this literature by documenting how geographically concentrated shocks like the fracking boom can have sustained and substantial consequences for local economies, which particularly benefit individuals from disadvantaged backgrounds.

II Background

Hydraulic fracturing or "fracking" refers to a set of technologies and techniques used to extract oil and natural gas from shale plays, which are dense, fine-grained rock formations that trap hydrocarbons within small, dispersed pockets. Shale plays are large formations, the Marcellus shale in particular stretches from West Virginia to New York and encompasses over 100,000 square miles. Figure 1c shows the boundaries of major US shale plays relative to the Opportunity Atlas mobility measure, where the Marcellus shale play in particular traces the contours of the most upwardly mobile parts of Pennsylvania and West Virginia.

Prior to improvements in wide-scale directional drilling and hydraulic fracturing, producers largely assumed shale play reserves were unusable. Fracking technological changes led to reassessments the U.S.'s proved reserves, defined as the amount of hydrocarbons that can be recovered from deposits with a "reasonable level of certainty". These increases match the spread of fracking technologies around the country (shown in Figure 2a), as new shale plays were surveyed and shown to be amenable to fracking techniques.[7]

[7] The EIA provides shape files defining every known shale play, which we use to identify counties that have any fracking potential. We obtained well-level production data on the near-universe of operational wells from Enverus, a private oil and gas software company, through their academic outreach initiative. These data include information on total monthly production, the latitude/longitude of each well, and the orientation of the wellbore, which we use to identify fracking wells. For all the analysis here, we do not consider the Antirim Shale in Michigan or the Montery

Actual fracking production is likely endogenous with respect to local labor market characteristics; for example, more economically advantaged areas may be better positioned to adopt the new technologies that enabled the fracking boom. On the other hand, the value of land is cheaper in rural areas, and there may be fewer political impediments to drilling. In fact, Appendix Table A2 shows that, while not being substantially different from low-production shale CZs, high productivity shale CZs are slightly negatively selected in terms of characteristics that are correlated with upward mobility. To isolate variation in fracking intensity based only on plausibly exogenous, geographic variation in fracking amenability over time, we follow the fracking literature (Kearney and Wilson, 2018; Feyrer et al., 2017) and create a measure of simulated fracking production by estimating the following equation:

$$ln(new\ value_{gt} + 1) = \alpha_g + \sum_{\tau=2001}^{2012} \sum_{j=1}^{J} \theta_{\tau j} * \mathbb{1}\{CZ\ g\ over\ shale\ play\ j\} * \mathbb{1}\{t = \tau\} + \upsilon_{gt} \quad (1)$$

where $ln(new\ value_{gt} + 1)$ is the (real, \$2010) dollar value of oil and natural gas from wells drilled in location g in year t. θ_{tj} captures the average effect of being over shale play j, and allows this effect to vary over time as both prices and technologies evolve. We also control for time-invariant location characteristics via α_g. We can then use these predicted values to calculate simulated production as follows:

$$sim.new\ value_{gt} = exp\left(\widehat{\alpha}_g + \sum_{\tau=2001}^{2012} \sum_{j=1}^{J} \widehat{\theta}_{\tau j} * \mathbb{1}\{CZ\ g\ over\ shale\ play\ j\} * \mathbb{1}\{t = \tau\}\right) - 1 \quad (2)$$

For all of the results, we divide this measure by the 1990 population to calculate the simulated value of production per capita in thousands of dollars. To capture the effects of the total exposure to the fracking boom, we use the total value of simulated production in place g from 2001 to 2012 in all the cross-sectional regressions.[8]

II.A Measuring Chinese Import Competition

Figure 2b shows the immediate, sustained drop in manufacturing employment in the U.S. between 2000 and 2001. (Pierce and Schott, 2016) documents that the fall in manufacturing employment was concentrated in industries heavily exposed to Chinese import competition as a result of the permanent normalization of trade relations with China in October 2000. Before normalization of

Shale in California. As of 2011, the official EIA estimates of shale oil and natural gas reserves do not consider either of these locations, nor has a fracking start time been identified for either shale play prior to 2013.

[8]The correlation between simulated and actual production is 0.73.

trade relations, which was conditional on China's entry into the World Trade Organization (WTO) at the end of 2001, tariffs on Chinese goods were conditional on annual approval from Congress.

The Smoot-Hawley Tariff Act, passed by Herbert Hoover in 1930 as a protectionist measure over the stringent protests of economists, set the second-highest level of tariff rates in U.S. history. These rates were automatically applied to products from non-market economies (including China). However, starting in 1974 with the passage of the Trade Act, the U.S. president could grant lower, normalized tariff rates to non-market economies, subject to renewal each year by congressional vote. Although this special exemption status was granted to Chinese goods each year from 1980 to 2001, the process was contentious,[9] and there was considerable uncertainty over whether the much higher Smoot-Hawley rates would come back into effect. Pierce and Schott (2016) and Handley and Limao (2017) both connect the removal of this uncertainty upon China's entry into the WTO to the large decline in U.S. manufacturing employment and nearly one-third of the rise in China's export growth.

To leverage plausibly exogenous variation in Chinese import exposure, we follow Pierce and Schott (2016) by exploiting the difference in tariff rates between the normalized, WTO rates that were permanently applied to Chinese goods in 2001 and the much higher Smoot-Hawley Tariff Act rates, which were set in 1930. Since these tariffs are set for specific industries (4-digit SIC codes) we follow Pierce and Schott (2016) by constructing a CZ-level weighted average measure of exposure as follows:

$$WTO\ Gap_g = \sum_i \frac{Employment_{ig}^{1990}}{Employment_g^{1990}} * (Smoot\text{-}Hawley\ Rate_i - WTO\ Rate_i) \tag{3}$$

where g indexes place and i indexes industries. $WTO\ Gap_g$ is an employment weighted measure of Chinese import competition, as captured by the difference between protectionist and free-trade tariff schemes.[10]

Figure 1d plots this tariff exposure measure, which indicates that the traditional manufacturing heartland of the Rust Belt and the South Atlantic were hardest hit by Chinese competition. A growing literature has used this spatial variation to explain negative social changes such as rises in crime (Che et al., 2018), falls in marriage (Autor et al., 2019), along with declines in standard measures of economic security, including relative increases in household debt (Barrot et al., 2022).

[9]From 1990-1992, the House voted to repeal the exemption on Chinese goods, but were overruled by the Senate.

[10]Employment counts at the county-industry level are available from the US County Business Patterns Database. Pierce and Schott (2016) provide the change in tariff rates at the industry-level as a result of China's entry into the WTO.

III Data

While all the data we consider exists at the county level, for the main results we focus on commuting zones (CZs), for two main reasons. First, due to sample limitations placed on the data to ensure more accurate measurements, a much larger fraction of the data from the Opportunity Atlas is missing for smaller, rural counties than for commuting zones.Secondly, Feyrer et al. (2017) document substantial geographic spillovers as a result of the fracking boom, where localities adjacent to fracking counties also saw employment and wage growth. Partly, this is likely due to the increased demand for trucking jobs; the operations of a single well can involve hundreds of commercial truck trips (Goodman et al., 2016) to haul the materials needed for hydraulic fracturing. By aggregating the data to CZs, we are better able to capture the potential beneficiaries of increased fracking production, although all the results are robust to focusing on the county-level measures, as shown in Appendix Table A3 and Appendix Table A4.

The measures of intergenerational mobility are taken from Chetty et al. (2014), and are calculated from restricted-access federal income tax records. The persistence of intergenerational income can be summarized by the rank-rank slope, which can be estimated by fitting a line through the position of children relative to the position of their parents in their respective income distributions. A flatter rank-rank slope implies that children's income is less dependent on their parent's income (less income persistence). Chetty et al. (2014) calculate this relationship for each county and commuting zone in the country using parent and children positions in the national income distribution.[11] Variation in income persistence across the U.S. is shown in Figure 1b, where it seems that children's income is most determined by their parents in the South and parts of the Rust Belt.

The intercept of the rank-rank relationship is equal to the expected outcome of a child born to parents at the bottom of the parental income distribution. This value characterizes an absolute measure of mobility, where higher values imply that low-income children born in a specific area are more likely to be better off in absolute terms than their peers born elsewhere. The intercept (absolute mobility) and the slope (income persistence) give parsimonious descriptions of mobility across different areas of the country.

Chetty et al. (2014) focus on measuring intergenerational mobility for the 1980-1982 birth cohort (hereafter referred to as "children"). Parents are the individual(s) who have claimed the children as dependents. Parental income is averaged from 1996-2000, when the children were 15-20 years old. Children's income is averaged from 2011-2012, when the children were 30-32 years old. Figure 2 emphasizes that the parental income, in terms of when it is calculated for either mobility measure

[11] Income is measured at the household level, and includes labor earnings, capital income, unemployment insurance, Social Security, and disability benefits. All income measures are pretax.

should be unaffected by either shock. Conversely, children's income is measured after all major shale plays adopted fracking at the height of the boom, after the substantial declines in manufacturing employment opportunities had already taken place.

Finally, we take yearly, county-level population estimates from the National Cancer Institute's Surveillance, Epidemiology and End Results (SEER) Program, which are updated annually to account for migration. Data on various county-level characteristics including labor force participation and marriage rates are obtained from the US Census Bureau's 1990 Decennial Census. We focus on the main social variables of interest discussed in Chetty et al. (2014).

We consider various baseline characteristics which may vary across shale and non-shale regions in Appendix Table A1. Shale CZs seem positively selected in terms of their non-shale counterparts. However, we show in Appendix Table A2 that the most productive fracking counties are somewhat negatively selected. Similarly, places with large manufacturing employment, may differ from one another for various reasons. Although this is ameliorated by the fact that we are using variation in tariff rates set in 1930 to scale the intensity of the manufacturing shock, Appendix Table A5 shows that there are non-insubstantial baseline differences between commuting zones that were more or less impacted by the China trade shock. Particularly, human capital measures are lower in heavily impacted CZs, and the broader negative selection may be explained by so called "domestic offshoring", where manufacturing shifted to the South Atlantic region before 2000 in search of lower wages (Fort et al., 2018). We explore the sensitivity of the results to the inclusion of these controls in Section IV, and specifically try to gauge the explanatory power of each shock relative to other factors in Section IV.B.

IV Empirical Strategy and Results

We estimate the reduced-form relationship between the total exposure to simulated fracking production and Chinese import competition on mobility using the following specification:

$$y_g = \alpha + \beta \sum_{2000}^{2012} sim.new\ value_g + \rho WTO\ Gap_g + X_g' \Omega + \epsilon_g \tag{4}$$

where each independent variable to have a mean of zero and a standard deviation of 1. β captures the effect of a standard deviation shift in simulated fracking production on the different mobility measures. We also include the $WTO\ Gap_g$, the employment-weighted measure of tariff changes discussed in Section II, to identify areas with larger shares of workers who were more likely to face job-losses as a result of industry-level competition with cheaper Chinese imports. In all regressions we include the characteristics of places discussed in Chetty et al. (2014) as being the most strongly correlated with the absolute upward mobility measure (represented by X_g') shown in Figure 3. However, because these controls are not exogenous with respect to parental location decisions, we also report estimates without controls.

Although we are unable to run a difference-in-differences style regression because we only observe each mobility measure at a single point in time, our main independent variables leverage both temporal and cross-sectional variation. Both variables are constructed as the change in the level of exposure to each shock from when parental income is measured to when children's income is measured. In each case, the level of exposure is determined by quasi-random variation in either pre-existing geological features or changes in official industry-specific tariff rates set decades earlier.

Table 1 shows results from Equation 4. Income persistence is the slope of the rank-rank relationship in each CZ, while absolute mobility is the average income rank of children born to parents at the 25^{th} percentile of the income distribution.[12] While declines in income persistence may be driven by worse outcomes for children born to high-income parents, a rise in absolute mobility at a given income level measures how well children do relative to similar peers.

Across all specifications, higher levels of simulated fracking production are associated with increases in absolute upward mobility. A SD shift in the measure of simulated fracking production leads to a 0.3 to 0.8 p.p. (or 0.6-1.8 percent) increase in the average income rank of children born to parents at the 25^{th} percentile of the income distribution. This result is significant considering fracking is only viable in certain areas of the country, as shown in Figure 2a and discussed below. Conversely, increased Chinese import exposure led to substantial declines in mobility, although this effect is mediated by the inclusion of controls and state fixed effects. Specifically, a SD shift in the measure of import competition leads to a decrease between 0.3 and 2.2 p.p. (or 0.6-5 percent) in the average income rank of children born to parents at the 25^{th} percentile of the income distribution.

We observe much larger effect sizes at the county-level, as shown in Appendix Table A3 potentially because the independent variables are measured with more precision.[13] In the specification with controls and state fixed effects, a standard deviation shift in exposure to either shock leads to similar changes in absolute upward mobility.

Unlike absolute mobility, the fracking boom does not have a robust effect on income persistence,

[12] Absolute mobility then is the slope of the rank-rank relationship multiplied by 25, and added to the intercept. In this sense, absolute mobility incorporates both the mean outcomes of children born to parents at the absolute bottom of the income distribution (the intercept), and the degree to which parental income translates to better child outcomes (the rank-rank slope).

[13] This statement is especially true for simulated production where there is substantial within-CZ heterogeneity in fracking potential.

with all specifications implying minimal effects of simulated production. This result may be due to the fact that the introduction of fracking increased incomes across the distribution. While fracking jobs are concentrated among low-skill workers Cascio and Narayan (2022) and Feyrer et al. (2017) found substantial positive spillovers into other local industries. Additionally, Hornbeck and Moretti (2018) find that homeowners benefit substantially from local total factor productivity shocks due to increased housing prices.[14]

Conversely, we see that the manufacturing bust led income to be more persistent, suggesting that the link between parents and children's incomes are stronger in CZs hit harder by the manufacturing bust. Autor et al. (2019) found that the Chinese import competition led to sustained losses in earnings across the income distribution, albeit with greater magnitude losses occurring at lower incomes. When incomes change for the lower portion of the income distribution the slope of the rank-rank coefficient increases. We find suggestive evidence of this claim when we examine the heterogeneity results by family income outlined in Appendix B1 as discussed below. Additionally, Corak and Piraino (2011) found substantial intergenerational transmission of manufacturing employers - if the manufacturing bust more dramatically limited the job finding potential of children from poorer households, one would expect increasing income persistence.

We can begin to compare the effect sizes of these labor demand shocks to those discussed in the literature by examining the magnitudes of the coefficients on each of the independent variables included in our specifications. Appendix Figures A2a and A2b plot the point estimates and confidence intervals for a standard deviation shift in each independent variable reported in Table 1. We find that in terms of absolute upward mobility, the effect sizes we estimate for both shocks are comparable to standardized shifts in the high school drop out rate and the social capital index.[15] These point estimates are also similar in magnitude to those reported when examining shifts in prenatal pollution exposure (Colmer et al., 2023), and crime (Sharkey and Torrats-Espinosa, 2017). In terms of relative mobility, a standardized shift in import competition causes the largest change, aside from the percent of single of mothers in a CZ.

We also show that the average effects reported in Table 1 vary across subgroups. While the publicly available version of estimates from Opportunity Insights cannot be disaggregated by gender or income, we can begin to get a sense of potential heterogeneous effects using estimates of "causal effects of place" calculated by Chetty and Hendren (2018). We outline this estimation procedure in Appendix B1. We find that the percent change in income associated with 20 years of exposure to a

[14]Bartik et al. (2019) found that housing prices increased by 5.7 percent in boom counties, and the local willingness to pay for fracking was $2,500 annually, per household.

[15]This index is calculated by Rupasingha et al. (2000), and includes information on voter turnout rates, the fraction of people who return census forms, and the various measures of participation in community organizations.

particular CZ is concentrated among boys from low-income parents. These results further highlight the magnitude of the mobility results. Despite the impacts of these shocks being concentrated among one gender, we still see large subsequent changes in intergenerational mobility.

IV.A Mechanisms

The most obvious channel through which the two labor demand shocks influence upward mobility is increased wage earnings and employment opportunities. Within an event-study context where 2000 is the last pre-treatment year, we replicate the earnings and employment effects of both shocks in Appendix Figure A1.[16] A standard deviation shift in simulated reserves leads to a roughly 3 percent increase in employment and earnings, with no sign of abatement by the end of the sample. A standard deviation shift in the $WTO\ Gap_g$ led to more immediate and dramatic changes, with close to a 5 percent reduction in both earnings and employment up to a decade after the initial shock. Figure A1 shows that both of these changes are robust to accounting for the other, suggesting that we are not conflating, for example, some pre-existing likelihood of being insulated from the China trade shock with the likelihood of discovering oil and natural gas.

Chetty et al. (2014) emphasizes the strong correlation of non-labor market factors like commute times and single motherhood with absolute mobility, but the labor demand shocks focused on here can have downstream consequences on these characteristics. Several papers have shown negative downstream effects of increased import competition from China on marriage (Autor et al., 2019), subsequent job churn (Autor et al., 2016) and even mortality (Pierce and Schott, 2020). To the extent that the loss of work eroded the social factors that contribute to mobility, negative labor demand shocks have an exacerbated impact on overall regional inequality.

For the fracking boom, Kearney and Wilson (2018) find that marriage rates do not change in response to fracking production, so household income is not mechanically increasing as more joint-income households form. Additionally, the human capital responses to the fracking boom were actually negative, as high school dropout rates increased in boom counties (Cascio and Narayan, 2022). Other research has shown that some areas, especially the Bakken shale in North Dakota, experienced substantial in-migration (Wilson, 2020), this mechanism biases the results away from finding that the fracking boom increased intergenerational mobility. The income measures used to calculate the mobility measures in Chetty et al. (2014) are based on the filing location of the parents *prior to the boom*. A child who moves to work for a fracking job in say, 2005, is still counted as

[16] We take total employment, and wages from the Quarterly Census of Employment and Wages (QCEW). The QCEW is produced by the US Bureau of Labor Statistics, which aggregates data from approximately 95% of employers in the country at the county-sector level.

resident of the origin CZ, so some of the beneficiaries of fracking jobs are contributing to income growth in non-fracking CZs. Additionally, true residents of fracking CZs would experience reduced wage growth as the supply of low-skill workers increases due to the migratory responses to the boom.

We begin to explore the role that changes in non-labor market outcomes, stemming from our two labor demand shocks, influence our estimates on intergenerational mobility by examining the relationship between increased import competition, the fracking boom, and changes in CZ-level measures of the social factors captured in Chetty et al. (2014). In this effort, we calculate the change in these social factors from 1990 to 2014 and re-run Equation 4 using data from the decennial census and American Community Survey.[17] Appendix Table A6 shows the results of this exercise. Consistent with the related literature, we find that the fracking boom had little effect on the non-labor market characteristics that could explain our findings.

We do find that exposure to increased import competition from China was associated with changes in the social factors identified as influencing upward mobility. A back-of-the-envelope calculation, using the coefficients from Chetty et al. (2014), suggests that the changes in population shares of Black residents and single mothers explain about 27% of the decline in upward mobility we estimate. While significant, these results suggest that the impact of increased import competition on upward mobility are not only the result of the downstream effects of the shock.

IV.B ANCOVA Analysis

While it is clear that both shocks led to substantial changes in absolute mobility, we may wonder how these effects compare with non-labor market factors known to be important for mobility, such as education and marriage rates. For the sake of comparisons, we focus on the same factors to those discussed in Chetty et al. (2014). First, we report analysis of covariance (ANCOVA) results, which decompose the variance of the mobility measures into variance explained by fracking, variance explained by other covariates, and residual variance.

Figure 3 shows the results of the ANCOVA decomposition for the lower 48 states. The symbols correspond to estimates of partial η^2, which is the share of the variance of the outcome of interest attributable to a specific covariate (the share of the R^2 explained). The bands represent 95 percent confidence intervals. The sign of the correlation with the outcome of interest is reported in parentheses next to each variable. Figure 3a shows that roughly 5 percent of the variation in absolute mobility can be explained by the fracking measure, while 10 percent can be explained by the China

[17] There are small differences in the characteristics we examine when compared to Chetty et al. (2014). For example, we are only able to observe average commute time rather than the share of the population commuting less than 15 minutes. Furthermore, we are unable to construct Gini coefficients in 2014 due to restrictions in data access.

trade measure. This proportion is very similar to the amount of variation explained by the percent of black residents and the value of the social capital index.

The single largest factor in explaining absolute mobility is the percent of single mothers. This is partially mechanical, since the mobility measures are calculated using household income. Additionally, a large body of research has documented that children growing up outside a stable, two parent household have worse outcomes along many dimensions (Brown, 2010; Watts-English et al., 2006). As with Table 1, Figure 3b shows that neither shock explains almost any of the national variation in income persistence (i.e. relative income). Commute time is also very important, and likely proxies for spatial mismatch.

Unlike the variation in fracking reserves/import competition, baseline CZ characteristics are not exogenous with respect to the mobility measures. Parents concerned with the opportunities available to their children would likely choose to locate in CZs with characteristics conducive to upward mobility. This sorting would likely lead to overestimating the importance of baseline covariates, and so would attenuate the amount of variance in mobility explained by the two labor demand shocks. This is because the location of parents is "locked in" by 2000, a year before any substantial evidence about the location or size of fracking reserves became common knowledge. The same argument holds for why parents or children moving away from either the Rust Belt or the South would attenuate the relevant effect sizes.[18]

The largest explanatory factor of income persistence is exposure to Chinese import competition, although the magnitude is indistinguishable from the proportion of variance explained by the percentage of single mothers. Conversely, fracking variation explains almost nothing of income persistence. We can also see that the R-squared is much smaller for income persistence, with only a little over half of the variance being explained by the included covariates.

V Discussion and Conclusion

In this paper, we show that absolute mobility for the 1980-1982 birth cohort, or the expected outcomes of children born to low-income parents, was substantively altered by the fracking boom

[18]Since shale CZs only account for one quarter of all CZs in the US, this cross-country analysis limits the explanatory power of fracking intensity. The results for the U.S. compare (conditional on covariates) shale CZs to the entire rest of the country. While this comparison is informative, it does not tell us about the explanatory power of the intensity of the fracking boom *within* areas directly able to benefit from production. To address this, we restrict my attention to shale CZs only in the Online Appendix, where we show that simulated fracking production is the single largest explanatory factor of the variation of absolute mobility within shale CZs, aside from marriage rates. Even within shale CZs, however, our results show that fracking intensity did not meaningfully affect the degree of income persistence between parents and their children.

and increased Chinese import competition. We show these effects were sizable, and not driven by pre-existing differences in characteristics predictive of mobility. The positive effects from the fracking boom are likely also not driven by any "virtuous cycle", where social factors positively related to mobility were impacted by the fracking boom, as other research finds no change in marriage rates and education *declines* in boom counties. Overall, fracking intensity and exposure to Chinese import competition explain close to 15% of the national variation in absolute upward mobility.

Our results indicate that local labor market conditions in the U.S. matter substantially for absolute upward mobility. However, we find less evidence that the fracking boom or the manufacturing bust altered the relationship between parental income and children's outcome. This result is very similar to Butikofer et al. (2025), who found that the oil boom in Norway broke the link between fathers and *grandsons* in terms of income persistence, but that income still persisted between fathers and sons, and between sons and grandsons.

While local labor markets clearly matter for mobility, it is unclear whether large positive shocks translate into sustained regional development. Black et al. (2005) found that a coal boom led to positive employment and earnings spillovers into other industries, but that the subsequent bust led to even larger *negative* spillovers. Precipitated in part by the COVID-19 pandemic, the fracking boom appears to be slowing, if not reversing (Elliott and Matthews, 2020). The evidence from this paper suggests that the South Atlantic region, where manufacturing employment was growing before China's entry into the WTO, suffered persistent losses which it had yet to recover from a decade out. Future research should seek to analyze the long-term consequences of temporary low-skill job booms on mobility in general, and how communities heavily invested in certain forms of employment can rebuild and re-skill to recover. Finally, continuing the work of understanding how social factors are shaped by labor demand shocks as in Kearney and Wilson (2018) and Autor et al. (2019) and how these two forces interact seems crucial to understanding upward mobility more broadly.

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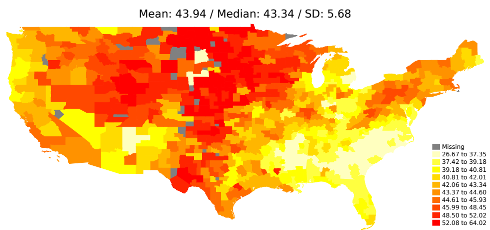
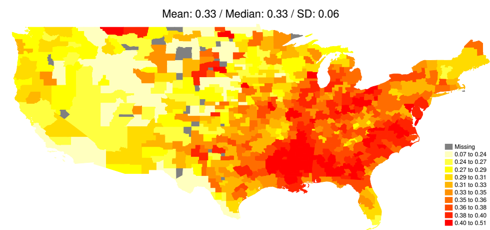
Figures

Figure 1: Geographic Variation in Mobility and Fracking/Chinese Competition Exposure

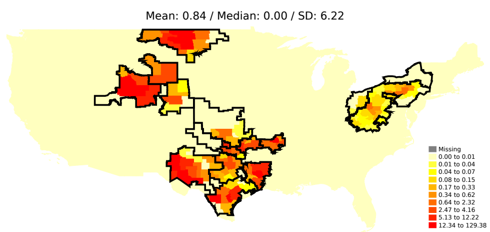
(a) Absolute Upward Mobility



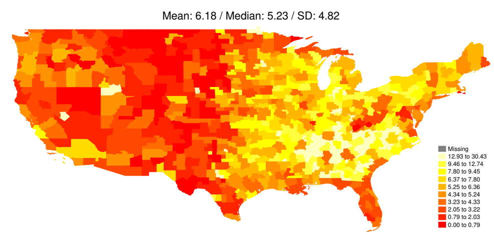
(b) Income Persistence



(c) Fracking Production and Shale Plays



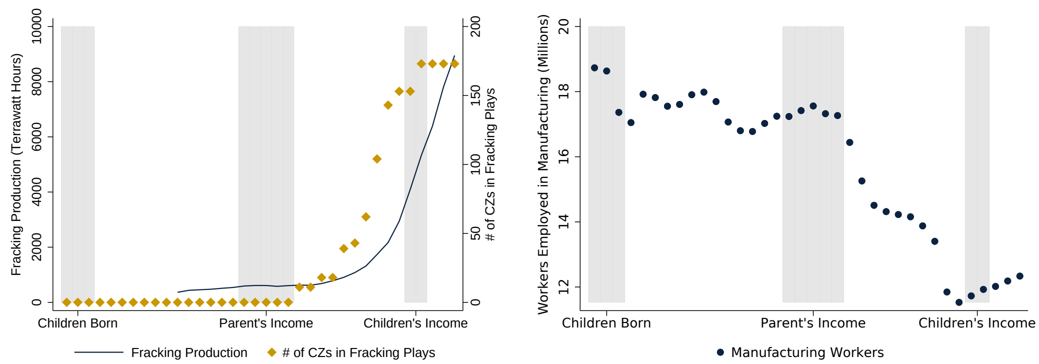
(d) WTO Tariff Gap



Notes: Panel A plots the deciles of "Absolute Upward Mobility" taken from Chetty et al. (2014) at the commuting zone level. Absolute Upward Mobility measures the expected rank in the national income distribution of a child (from the 1980-1982 birth cohort) born to parents at the 25^{th} percentile of the national parental income distribution. Darker values indicate that, on average, children born to low-income parents achieved higher positions in the national distribution of children's income than their peers born to low-income parents elsewhere. Panel B maps the deciles of differences between the 2000 and 2012 employment to population ratio, where employment is limited to only natural resource extraction and manufacturing. The employment data come from the QCEW, while the contemporaneous population measures come from SEER.

Figure 2: Opportunity Atlas Cohort Exposure to the Fracking Boom and Manufacturing Bust

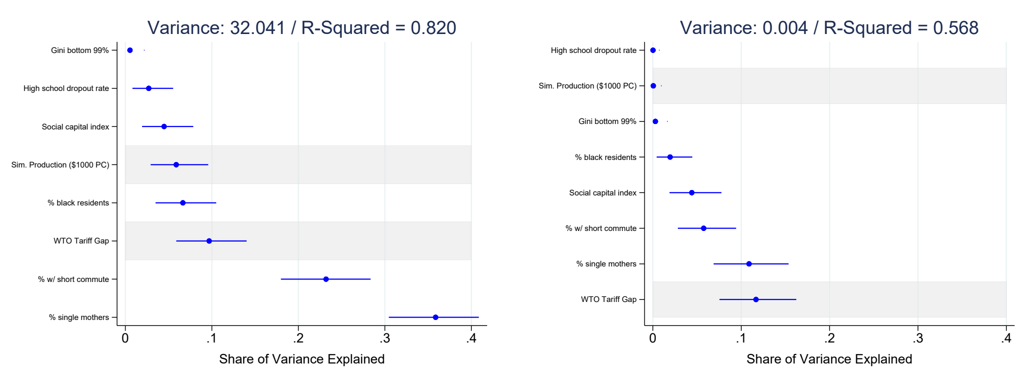
(a) Fracking Production and Adoption (b) Manufacturing Employment



Notes: Panel A plots the national sum of production from fracking wells, which is calculated from monthly, well-level production data provided by Enverus. Fracking wells are defined by the orientation of the wellbore, and we include both horizontal and directional wells. The diamonds indicate the number of commuting zones which had begun fracking by that year, and the fracking start dates come from Bartik et al. (2019). Panel B plots the number of U.S. workers employed in manufacturing, which was obtained from the Federal Reserve Economic Database (FRED). The shaded bars indicate times important for the creation of the mobility measures for the 1980-82 birth cohort from the Opportunity Atlas. Parental income is measured from 1996-2000, while children's income is measured from 2011-2012.

Figure 3: ANCOVA Results - Lower 48 States

(a) Absolute Mobility (b) Income Persistence



Notes: These figures show the results of an ANCOVA analysis, where each symbol corresponds to η^2, or the amount of the variation in the outcome of interest explained by a specific covariate. The bands represent 95 percent confidence intervals. The included covariates are the same included as controls in A1, and the R-Squared measures correspond to in Panel A and Panel B are identical to those reported in column 2 and column 4, respectively.

Tables

Table 1: The Fracking Boom and Manufacturing Bust - Changes in Mobility

	Absolute Upward Mobility			Income Persistence		
	(1)	(2)	(3)	(4)	(5)	(6)
SD Shift: Sim. Production	0.807***	0.597***	0.335**	-0.003*	-0.001	-0.000
	[0.099]	[0.110]	[0.098]	[0.001]	[0.001]	[0.001]
SD Shift: WTO Tariff Gap	-2.201***	-0.900***	-0.306*	0.029***	0.018***	0.010***
	[0.399]	[0.152]	[0.134]	[0.004]	[0.002]	[0.002]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	44.03	44.03	44.03	0.33	0.33	0.33
R-Squared	0.177	0.820	0.882	0.200	0.568	0.676
Observations	693	693	690	693	693	690

Notes: Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. *** p<0.001, ** p<0.01, * p<0.05. The SD shifts for the even columns are calculated as linear combinations of the regression estimates.

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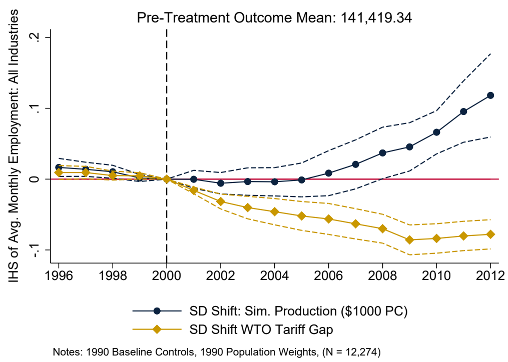
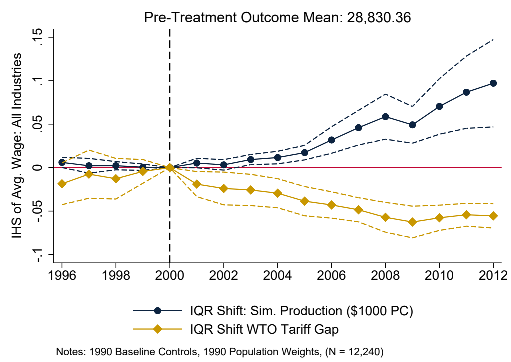
Figure A1: Fracking vs. Chinese Import Competition - Employment and Earnings

(a) Employment



(b) Earnings

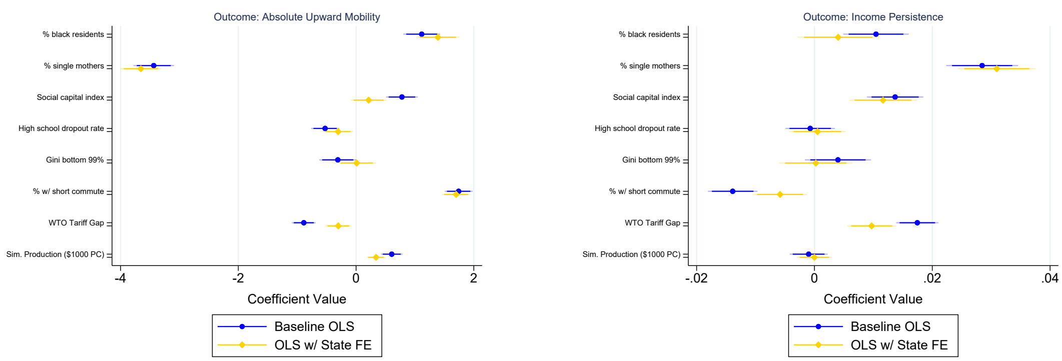


Notes: Panel A and Panel B report event-study coefficients for the impacts of simulated fracking (dark blue circles) and WTO Tariff Gap (gold diamonds) on employment and earnings, respectively. Each circle/diamond corresponds to a scaled point estimate, while the dotted lines represent 95 percent confidence intervals. For Panel A, the outcome of interest is the inverse hyperbolic sine of the average monthly number of workers employed in all industries. For Panel B, the outcome of interest is the average weekly wage multiplied by 52, which approximates the average annual wage. All regressions include the controls shown in Appendix Table A1. The 1996-2000 average of each outcome of interest is reported as the pre-treatment outcome mean.

Figure A2: Coefficient Values

(a) Absolute Upward Mobility

(b) Income Persistence



Notes: This figure plots the point estimate, 90% and 95 percent confidence intervals for each independent variable included in Table 1. All variables are normalized by subtracting their mean value and dividing by the standard deviation.

Table A1: Summary Statistics - Differences by Shale Presence

	Some Fracking	No Fracking	Difference (Some - None)
	(1)	(2)	(3)
Absolute Upward Mobility (+)	46.24	43.34	2.90***
	(4.92)	(5.70)	[0.46]
Income Persistence (-)	0.32	0.33	-0.01
	(0.06)	(0.05)	[0.01]
% w/ Short Commute (+)	47.97	44.32	3.65**
	(14.25)	(13.26)	[1.22]
Gini Bottom 99% (-)	0.30	0.30	-0.00
	(0.05)	(0.06)	[0.00]
High School Dropout Rate (-)	-0.01	0.00	-0.01***
	(0.02)	(0.02)	[0.00]
Social Capital Index (+)	0.18	0.17	0.01
	(1.12)	(1.35)	[0.10]
% Single Mothers (-)	18.81	20.62	-1.82***
	(3.80)	(5.66)	[0.38]
% Black Residents (-)	4.32	9.10	-4.78***
	(5.51)	(13.60)	[0.72]
Observations	173	549	722

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$. This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones which intersect in whole or in part with a shale play (Any Fracking) and those commuting zones which do not (No Fracking). The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.

Table A2: Summary Statistics - Differences Within Shale CZs

	Above Median Fracking	Below Median Fracking	Difference
	(1)	(2)	(3)
Absolute Upward Mobility (+)	46.62	45.87	0.74
	(4.96)	(4.89)	[0.77]
Income Persistence (-)	0.31	0.33	-0.01
	(0.06)	(0.05)	[0.01]
% w/ Short Commute (+)	48.28	47.67	0.61
	(13.88)	(14.70)	[2.17]
Gini Bottom 99% (-)	0.31	0.29	0.02*
	(0.05)	(0.04)	[0.01]
High School Dropout Rate (-)	-0.00	-0.01	0.01**
	(0.02)	(0.01)	[0.00]
Social Capital Index (+)	-0.10	0.46	-0.55**
	(1.05)	(1.13)	[0.17]
% Single Mothers (-)	19.20	18.41	0.79
	(3.71)	(3.86)	[0.58]
% Black Residents (-)	4.79	3.84	0.95
	(6.62)	(4.07)	[0.83]
Observations	87	86	173

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$ This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones that intersect with a shale play by the intensity of fracking production. The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.

Table A3: The Fracking Boom and Manufacturing Bust - Absolute Mobility

	Absolute Upward Mobility					
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shale Play	2.590**	1.467***	0.927***			
	[0.887]	[0.405]	[0.249]			
> Median Manu. Share 2000	-1.410*	-1.570***	-0.585**			
	[0.692]	[0.261]	[0.185]			
SD Shift: Sim. Production				2.733***	2.292***	1.572***
				[0.521]	[0.371]	[0.426]
SD Shift: WTO Tariff Gap				-1.928***	-1.065***	-0.455***
				[0.286]	[0.111]	[0.106]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	43.46	43.46	43.46	43.46	43.46	43.46
R-Squared	0.0504	0.7114	0.7958	0.1312	0.7212	0.7987
Observations	2,748	2,748	2,747	2,748	2,748	2,747

Notes: Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. *** p<0.01, ** p<0.05, * p<0.1. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.

Table A4: The Fracking Boom and Manufacturing Bust - Income Persistence

	Absolute Upward Mobility					
	(1)	(2)	(3)	(4)	(5)	(6)
Any Shale Play	-0.002	0.012*	-0.001			
	[0.008]	[0.006]	[0.005]			
> Median Manu. Share 2000	0.036***	0.033***	0.016***			
	[0.008]	[0.005]	[0.004]			
SD Shift: Sim. Production				-0.002	0.001	-0.002
				[0.008]	[0.006]	[0.008]
SD Shift: WTO Tariff Gap				0.026***	0.019***	0.011***
				[0.003]	[0.002]	[0.002]
Controls?	No	Yes	Yes	No	Yes	Yes
State Fixed Effects?	No	No	Yes	No	No	Yes
Outcome Mean	0.33	0.33	0.33	0.33	0.33	0.33
R-Squared	0.063	0.375	0.487	0.126	0.383	0.493
Observations	2,748	2,748	2,747	2,748	2,748	2,747

Notes: Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. *** p<0.01, ** p<0.05, * p<0.1. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.

Table A5: Summary Statistics - Differences by Chinese Competition Exposure

	Above Median *WTO Gap*	Below Median *WTO Gap*	Difference
	(1)	(2)	(3)
Absolute Upward Mobility (+)	42.44	45.72	-3.28***
	(5.05)	(5.79)	[0.41]
Income Persistence (-)	0.35	0.30	0.05***
	(0.05)	(0.06)	[0.00]
% w/ Short Commute (+)	40.59	49.80	-9.21***
	(9.61)	(15.32)	[0.95]
Gini Bottom 99% (-)	0.31	0.30	0.01
	(0.06)	(0.06)	[0.00]
High School Dropout Rate (-)	0.00	-0.00	0.01**
	(0.02)	(0.02)	[0.00]
Social Capital Index (+)	-0.02	0.37	-0.39***
	(1.13)	(1.41)	[0.10]
% Single Mothers (-)	21.22	19.16	2.07***
	(5.59)	(4.84)	[0.39]
% Black Residents (-)	11.12	4.80	6.32***
	(14.63)	(8.40)	[0.89]
Observations	361	361	722

Notes: * $p < .05$, ** $p < .01$, *** $p < .001$ This table shows the difference in mobility and the major correlates with absolute mobility discussed in Chetty et al. (2014) between commuting zones that intersect with a shale play by the intensity of fracking production. The sign of the correlation with absolute upward mobility is reported in parentheses next to each variable. Means of the measures are reported in the first two columns, and standard deviations are reported below in parentheses. Column 3 reports the difference between the means in Column 1 and Column 2, and the relevant standard error on the t-test of the significance of this difference is reported below in brackets.

Table A6: The Fracking Boom and Manufacturing Bust - Potential Mechanisms

	Δ Commute Time	Δ % Black Residents	Δ % Less than HS	Δ % Single Mother	Δ Social Capital Index
	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline Specification					
SD Shift: Sim. Production	-0.218	-0.030	-0.148	-0.020	-0.039
	(0.405)	(0.064)	(0.108)	(0.016)	(0.033)
SD Shift: WTO Tariff Gap	1.367***	-0.155*	-1.489***	0.065***	-0.008
	(0.405)	(0.064)	(0.108)	(0.016)	(0.033)
R-squared	0.017	0.008	0.209	0.025	0.002
Observations	722	722	722	722	722
Panel B: Specification With State Fixed Effects					
SD Shift: Sim. Production	-0.074	0.015	0.059	-0.030	-0.073***
	(0.384)	(0.062)	(0.094)	(0.016)	(0.026)
SD Shift: WTO Tariff Gap	-0.756	-0.413***	-0.965***	0.049*	-0.032
	(0.512)	(0.083)	(0.125)	(0.021)	(0.034)
R-squared	0.213	0.213	0.495	0.239	0.490
Observations	719	719	719	719	719
1990 Outcome Mean	84.15	7.75	18.23	2.10	0.17

Notes: Table notes here.

Table A7: Values of δ: Oster (2019) Bounds

	Delta: w/o State FE	Delta: with State FE
	(1)	(2)
Sim. Production	5.67	3.08
WTO Tariff Gap	1.80	0.50
% w/ Short Commute	1.12	1.10
Gini Bottom 99%	0.12	-0.00
High School Dropout Rate	0.53	0.29
Social Capital Index	0.46	0.11
% Single Mothers	0.70	0.77
% Black Residents	-0.41	-0.45

Notes: This table reports the values of δ such that the coefficient for each independent variable is equal to zero, following the method outlined in Oster (2019). These values are calculating using the psacalc command in Stata, assuming a maximum R-squared value of 1.

Table A8: The Fracking Boom and Manufacturing Bust - Robustness by CZ Size

	Absolute Upward Mobility			Income Persistence		
	Full Sample	Pop. $\geq$ Median	Pop. $\geq 75^{th}$ Percentile	Full Sample	Pop. $\geq$ Median	Pop. $\geq 75^{th}$ Percentile)
	(1)	(2)	(3)	(4)	(5)	(6)
SD Shift: Sim. Production	0.335**	1.150*	1.973*	-0.000	0.005*	0.000
	[0.098]	[0.469]	[0.841]	[0.001]	[0.002]	[0.010]
SD Shift: WTO Tariff Gap	-0.306*	-0.509**	-0.570*	0.010***	0.124**	0.010***
	[0.134]	[0.151]	[0.210]	[0.002]	[0.002]	[0.004]
Outcome Mean	44.03	41.62	40.80	0.33	0.34	0.34
R-Squared	0.882	0.869	0.847	0.676	0.791	0.785
Observations	690	358	171	690	358z	690

Notes: Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. *** p<0.001, ** p<0.01, * p<0.05. The SD shifts for the even columns are calculated as linear combinations of the regression estimates.

B1 Appendix - Heterogeneity by Gender and Income

To further investigate the effects of the boom and bust on children from different parental backgrounds, we also consider the "causal effects of place" calculated by Chetty and Hendren (2018). Using similar individual-level tax data as in the mobility measures, Chetty and Hendren (2018) estimates the percent change in income that can be causally linked to where children grew up. Briefly, these causal effects are estimated by leveraging variation in the timing of moves across CZs, and by comparing outcomes for children *within* families based on the age of the child at the time of the move. We take as given that these measures represent a reasonable approximation of the causal effects of place. We focus on the percent change in income associated with 20 years of exposure to a particular CZ, which approximates the effect of spending one's entire childhood in the same place. All results are relative to the population-weighted average CZ in the country.

We report estimates from Equation 4 for boys and girls born to low-income parents in Appendix Table B1. Unsurprisingly, the income effects of the fracking boom are entirely concentrated among boys. Boys from low-income backgrounds experience large increases in income relative to the average CZ. The declines in earnings potential among children born to poorer households driven by Chinese import competition are also very large, but not robust to the inclusion of state fixed effects. For both shocks, the effects on female children are inconsistent, and flip sign and significance with the inclusion of state fixed effects. These results both confirm that we are seeing the result for exactly the group we should expect, and highlight the magnitude of the mobility results. Although the effect of these shocks is highly concentrated among one gender, we still see large subsequent changes in intergenerational mobility. For children born to high-income parents, shown in Appendix Table B2, the fracking results are roughly similar, but the negative impact of the manufacturing bust on high-income children is more muted and statistically insignificant.

Chetty and Hendren (2018) show that the "causal effects of place" decline linearly with the age of exposure, but are still relevant for influencing earnings later in life until age 23. To the extent that some commuting zones experience immediate effects from both shocks in the early 2000's, our results are unable to disentangle the direct effect on children's mobility through local labor market conditions in adulthood and the residual childhood exposure effects of place. The youngest children in the 1980-1982 cohort are 19 in 2001, and so children experience at most 4 years of childhood exposure effects, given that the first treatment year for both shocks is 2001.

Table B1: % Income Change from 20 Years of Exposure - Children Born to Low-Income Parents

	All Kids		Girls		Boys	
	(1)	(2)	(3)	(4)	(5)	(6)
SD Shift: Sim. Production	0.633**	0.425*	0.026	-0.035	1.095*	0.776*
	[0.232]	[0.170]	[0.136]	[0.093]	[0.436]	[0.321]
SD Shift: WTO Tariff Gap	-1.465***	-0.376	-0.950**	0.158	-1.782***	-0.829
	[0.277]	[0.338]	[0.325]	[0.294]	[0.422]	[0.490]
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects?	No	Yes	No	Yes	No	Yes
Outcome Mean	0.57	0.56	-3.14	-3.18	3.64	3.65
R-Squared	0.706	0.790	0.462	0.716	0.674	0.738
Observations	672	669	673	670	676	673

Notes: Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. *** p<0.01, ** p<0.05, * p<0.1. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.

Table B2: % Income Change from 20 Years of Exposure - Children Born to High-Income Parents

	All Kids		Girls		Boys	
	(1)	(2)	(3)	(4)	(5)	(6)
SD Shift: Sim. Production	0.609**	0.345**	0.043	-0.310*	0.942**	0.792**
	[0.226]	[0.099]	[0.180]	[0.150]	[0.313]	[0.229]
SD Shift: WTO Tariff Gap	-0.122	0.299	0.424	0.627	-0.512	-0.037
	[0.288]	[0.218]	[0.373]	[0.340]	[0.297]	[0.282]
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects?	No	Yes	No	Yes	No	Yes
Outcome Mean	-1.08	-1.12	-3.87	-3.93	1.30	1.29
R-Squared	0.476	0.708	0.363	0.642	0.485	0.629
Observations	672	669	673	670	676	673

Notes: Heteroskedacity-robust standard errors clustered at the state-level are reported in brackets beneath each point estimate. *** p<0.01, ** p<0.05, * p<0.1. The IQR shifts for the even columns are calculated as linear combinations of the regression estimates.